

CUARewardBench: A Benchmark for Evaluating Reward Models on Computer-using Agent

Youtu-Agent Team*

Computer-using agents (CUAs) enable task completion through natural interaction with operating systems and software interfaces. While script-based verifiers are widely adopted for evaluation, they suffer from limited scalability and inability to provide step-wise assessment. Reward models offer promising alternatives, but their effectiveness on CUA evaluation remains largely underexplored. To address this gap, we present **CUARewardBench**, comprising four key contributions: **(1) First-ever Comprehensive CUA Reward Benchmark:** We introduce the first benchmark for evaluating both outcome reward models (ORM) and process reward models (PRM) on CUA tasks, enabling systematic assessment across trajectory-level and step-level evaluation. **(2) Diverse, Practical and Reliable Dataset:** CUARewardBench encompasses trajectories from 10 software categories and 7 agent architectures with varying performance levels (25.9%-50.8% success rates). All trajectories are expertly annotated through carefully designed protocols, with rigorous quality control to ensure reliability and practical applicability. **(3) Comprehensive Analysis and Insights:** Through extensive experiments across 7 vision-language models and 3 prompt templates, we reveal critical limitations of current CUA RMs, including insufficient visual reasoning capabilities, knowledge deficiencies, and the superiority of general VLMs over specialized CUA models for reward evaluation. **(4) Unanimous Prompt Ensemble (UPE):** Based on the insights from our comprehensive analysis, we propose UPE, a novel ensemble method that significantly enhances reward model reliability through strict unanimous voting and strategic prompt-template configurations. UPE achieves 89.8% precision and 93.3% NPV for ORM, and 81.7% precision and 85.1% NPV for PRM, substantially outperforming single VLMs and traditional ensemble approaches. In a short, this work introduces **both a comprehensive benchmark and a novel ensemble method** that substantially enhances CUA reward model reliability.

 **Date:** October 19, 2025

 **Correspondence:** haojialin@tencent.com

1 Introduction

Computer-using agents (CUAs) represent a significant advancement in artificial intelligence, enabling large language models to interact directly with operating systems and software interfaces to accomplish complex tasks autonomously. Recent advances from contemporary agents including OpenAI’s Operator [1] and UITARS-2 [2] have demonstrated promising performance across diverse desktop scenarios.

Evaluating CUA performance presents unique challenges that extend beyond traditional language model assessment. While OSWorld benchmark [3] initially employed manually predefined scripts for trajectory verification, this approach incurs prohibitively high costs of manual annotation and is proved inadequate for scaling-up. Consequently, VLM-based reward models (RMs) have emerged as a cost-effective alternative for trajectory evaluation. The growing demand for CUA reward models stems from two critical needs: trajectory filtering to identify successful executions for off-line expert imitation as cold-start [4, 5, 6, 7], and providing reward signals for online agent reinforcement learning (RL) [6, 2]. These models must

*Full author list in contributions.

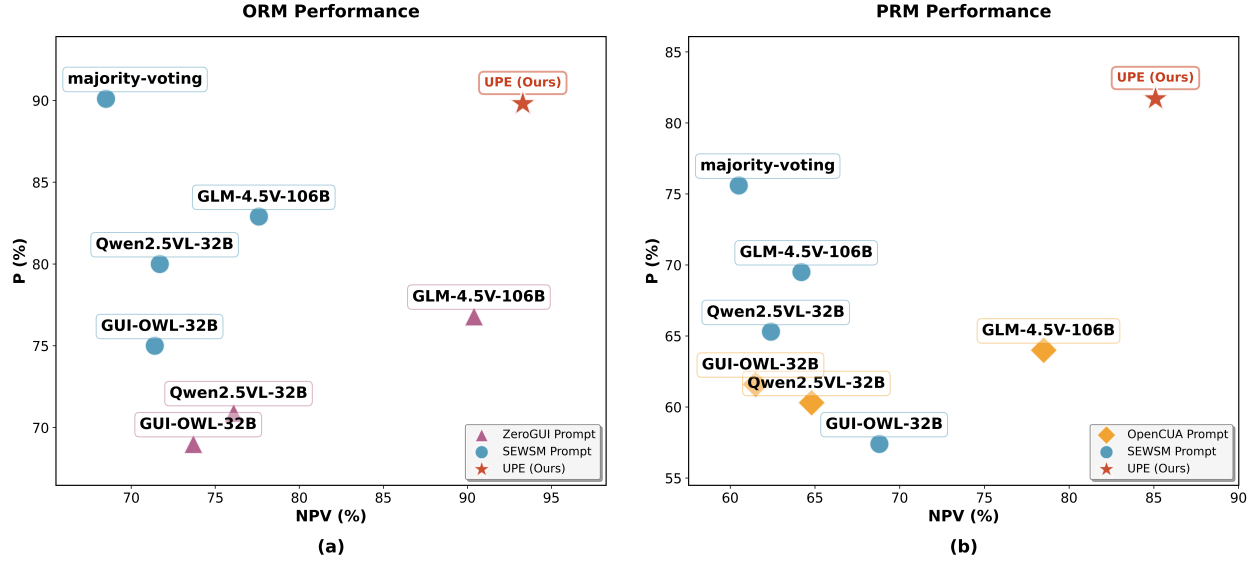


Figure 1. UPE achieves superior reward model reliability. Performance comparison on ORM and PRM tasks shows that our proposed UPE (red star) simultaneously achieves high precision and NPV, significantly outperforming single VLMs with different prompts and traditional ensemble methods (majority-voting). The upper-right positioning demonstrates UPE’s effectiveness in balancing positive and negative prediction accuracy. Details of UPE are discussed in Section 3.5.

evaluate both outcome success (whether the agent accomplished the task) and stepwise correctness (whether individual actions contribute to the goal). For a comprehensive review of related work, see Section 7.1. However, the effectiveness of existing reward models for computer-using agents remains largely unverified. While several recent works have proposed VLM-based reward models for CUA evaluation [4, 5, 2], many lack open-source implementations or detailed methodological descriptions, hindering systematic assessment and community-wide exploration of the capabilities of CUA RMs. This gap underscores the urgent need for standardized benchmarks that can rigorously evaluate and advance computer-using agent reward models.

To address these challenges, we present a systematic investigation into computer-using agent reward models through both benchmark construction and comprehensive evaluation. Our investigation comprises three complementary components. **First, we establish a rigorous evaluation framework by constructing CUARewardBench**, a benchmark specifically tailored to the unique requirements of CUA reward modeling (Figure 2). The benchmark design prioritizes three key aspects: *ecological validity* through diverse desktop software interactions that reflect real-world agent deployment scenarios, *comprehensive coverage* by incorporating trajectories from agents with varying architectural paradigms and capability levels, and *multi-granularity assessment* enabling evaluation of both trajectory-level outcomes and step-level correctness. **Second, we conduct systematic empirical analysis** to identify the critical factors determining reward model effectiveness, characterize their failure modes through detailed error analysis, and explore ensemble strategies that can enhance model reliability by leveraging complementary strengths of different approaches. These analyses reveal fundamental limitations in current approaches and provide insights into the design space for more reliable reward models. **Third, building upon these findings, we propose Unanimous Prompt Ensemble (UPE)**, a novel ensemble method that significantly enhances reward model reliability through strategic unanimous voting and diversified prompt-template configurations (Figure 1). As demonstrated in our experiments, UPE achieves substantial improvements over both single VLMs and traditional ensemble approaches, addressing the critical limitations identified through our empirical analysis.

This integrated approach—from benchmark construction to empirical analysis to method development—enables us to provide both a standardized evaluation testbed for the community and an immediately deployable solution for enhancing CUA reward model reliability. The main contributions of this paper are summarized as follows:

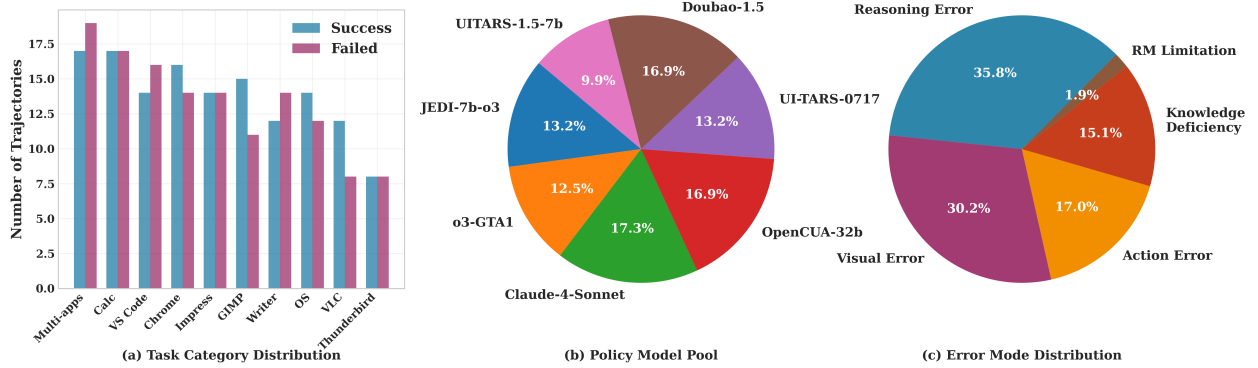


Figure 2. CUARewardBench dataset characteristics and selected experimental findings: (a) Task distribution of trajectory annotations across 10 software categories (Section 2.3), (b) policy model diversity in our benchmark (Section 2.2), and (c) key error modes identified in our evaluation experiments (Section 4).

- First-ever Comprehensive CUA Reward Benchmark:** We propose CUARewardBench, the first comprehensive benchmark specifically designed for evaluating both ORM and PRM on CUA trajectories. The benchmark comprises 272 trajectory success annotations and 346 step correctness annotations (Table 2), providing a rigorous testbed for systematic assessment of reward model capabilities across both trajectory-level and step-level verification.
- Diverse, Practical and Reliable Dataset:** CUARewardBench exhibits three key strengths that establish it as a rigorous evaluation framework. First, *diversity*: comprehensive task coverage across 10 software categories and trajectories from 7 distinct policy models with varying capabilities (Section 2.2). Second, *practicality and challenge*: carefully designed protocols for trajectory selection, key step identification, and annotation standards that capture realistic failure modes and critical decision points. Third, *reliability*: extensive human validation and multi-stage quality control to ensure annotation consistency and practical applicability (Section 2.3).
- Comprehensive Analysis and Insights:** Through extensive experiments across 7 state-of-the-art vision-language models and 3 prompt templates, we reveal that verification asymmetry challenges are significantly weakened in CUA tasks, with visual reasoning capability emerging as the overwhelmingly critical factor that dominates specialized training approaches (Section 3). Error analysis of 53 failure cases identifies reasoning errors (35.8%) and visual understanding errors (30.2%) as primary failure modes, providing actionable insights for future development (Section 4).
- Unanimous Prompt Ensemble (UPE):** We propose UPE, a novel ensemble method that significantly enhances reward model reliability for CUA tasks through strict unanimous voting and strategic prompt-template configurations (Section 3.5). As demonstrated in Figure 1, UPE achieves 89.8% precision and 93.3% NPV for ORM, and 81.7% precision and 85.1% NPV for PRM, substantially outperforming single VLMs with different prompts and traditional ensemble methods such as majority voting. This contribution provides a practical and immediately deployable solution for improving the reliability of reward-based CUA training pipelines.

2 CUARewardBench

This section presents the construction and characteristics of CUARewardBench, our comprehensive benchmark for evaluating reward models in computer-using agent tasks. We begin by formalizing the problem setting and defining key concepts in Section 2.1. Section 2.2 details our trajectory collection methodology, including task selection, policy model diversity, and data curation protocols. Section 2.3 describes our

rigorous annotation process, quality control measures, and the resulting dataset statistics. Figure 2 provides an overview of the dataset characteristics and key findings from our evaluation experiments.

2.1 Problem Formulation

Trajectory Definition. Let q denote the instruction given by user, o_i denote a system state observation at step i , and a_i represent an executable action in an operating environment $\mathcal{E}$ such that $o_{i+1} = \mathcal{E}(o_i, a_i)$. A computer-using agent trajectory is defined as the sequence:

$$\mathcal{T} = \{q, o_1, (r_1, a_1), o_2, (r_2, a_2), \dots, (r_{n-1}, a_{n-1}), o_n\} \quad (1)$$

where r_i is the agent’s reasoning for action a_i , and o_n is the terminal state. Each state observation o_i contains a **single RGB screenshot** of the current interface, consistent with current reward model practices that use visual inputs exclusively.

Reward Model Formulation. Given trajectory $\mathcal{T}$, a reward model $\mathcal{R}$ predicts:

$$\hat{\mathcal{A}} = \mathcal{R}(\mathcal{T}) = (\hat{s}, \{\hat{c}_1, \dots, \hat{c}_{n-1}\}) \quad (2)$$

where $\hat{s} \in \{0, 1\}$ indicates trajectory success (1 = success, 0 = failure), and $\hat{c}_i \in \{0, 1\}$ denotes step correctness (1 = correctness, 0 = non-correctness). In recent researches [8, 6, 5, 4, 2], $\mathcal{R}$ is exclusively implemented using VLMs as the core evaluation engine.

The following sections detail the construction of CUARewardBench: Section 2.2 describes the curation process for trajectories $\mathcal{T}$, while Section 2.3 presents the ground truth annotation methodology for $\hat{s}$ and $\hat{c}_i$.

2.2 Trajectory Collection.

Tasks and Environments. We build CUARewardBench upon OSWorld [3], a widely-adopted benchmark that provides comprehensive evaluation environments for computer-using agents across diverse desktop applications. OSWorld is particularly well-suited for our purposes due to its widespread adoption in the research community and its comprehensive coverage of realistic computer interaction scenarios. The benchmark encompasses 10 common software applications across different task categories, including Chrome, Thunderbird, LibreOffice Writer, LibreOffice Calc, LibreOffice Impress, VS Code, GIMP, VLC, and OS operations, providing a rich ecosystem for evaluating computer-using agent capabilities. CUARewardBench cover all 10 task categories to provide comprehensive evaluation across the complete spectrum of computer-use scenarios. To ensure benchmark quality and maintain evaluation reliability, we systematically exclude tasks marked as infeasible in the original OSWorld dataset to avoid introducing evaluation noise from inherently unsolvable scenarios.

Policy Model Pool. To ensure trajectory diversity and comprehensive coverage of agent capabilities, we employ 7 distinct CUA models with 10 different configurations (some agents vary in maximum step limits). As shown in Table 1, our agent selection follows two key principles: 1) *Architectural Diversity*: We include both single-model approaches and agentic frameworks to capture different decision-making paradigms. 2) *Performance Spectrum*: Our selected agents span success rates from 25.9% to 50.8% on OSWorld, ensuring comprehensive coverage of capability levels.

This dual consideration ensures trajectory diversity by capturing a wide spectrum of decision-making patterns and failure modes, providing a robust foundation for evaluating reward model generalization.

Agent Model	Arch	SR (15-S)	SR (50-S)	Traj
JEDI-7b-o3 [9]	Framework	42.4	50.8	36
o3-GTA1 [10]	Framework	-	48.8	34
Claude-4-Sonnet [11]	Single	31.3	44.0	47
OpenCUA-32b [7]	Single	28.3	33.9	46
UI-TARS-0717 [12]	Single	31.9	-	36
Doubao-1.5-Thinking [13]	Single	28.3	-	46
UITARS-1.5-7b [12]	Single	25.9	-	27
Oracle SR / Total Num	-	72.3		272

Table 1. Policy model pool of for dataset curation: agent architecture, success rates on OSWorld across different step limits, and trajectory collection counts.

Additionally, our diverse agent pool enhances task coverage for successful trajectories, achieving an oracle success rate of 72.3% and establishing a solid data foundation for subsequent trajectory curation.

Trajectory Selection Criteria. Building upon the established agent configurations, we leverage pre-collected trajectories¹ from OSWorld-verified [14] across all 10 task categories and 7 agent models. Our trajectory curation follows systematic criteria designed to ensure benchmark quality and evaluation comprehensiveness:

- *Task Category Balance:* We maintain balanced distribution across software categories to enable comparative analysis of reward model performance.
- *Success-Failure Balance:* We ensure proportional coverage of successful and failed trajectories to evaluate reward models’ discriminative capabilities across both outcome types.
- *Difficulty Control:* We exclude trajectories where no agent succeeds (too difficult) or where 8+ agent configurations succeed (too easy), ensuring moderate difficulty levels that provide meaningful evaluation challenges.
- *Step Count Constraint:* We select trajectories containing fewer than 25 steps, as this threshold accommodates most task completions while maintaining manageable annotation costs.

2.3 Annotation

Trajectory Success. Although OSWorld provides script-based trajectory success evaluation, we employ human annotation to ensure annotation reliability and accuracy. Annotators evaluate trajectory success based on two primary criteria:

- *Instruction Consistency:* Whether the agent successfully transitions the computer’s final state to match the requirements specified in the instruction.
- *Harmful Side Effects:* Whether the agent causes unintended changes to the computer’s final state that are not required by the instruction and would require additional corrective actions to resolve. Note that redundant but harmless operations (e.g., extra clicks on desktop) are not considered violations of this criterion.

Step Correctness. We evaluate step correctness based on a single criterion: whether the step’s execution positively contributes to trajectory success. Formally, let o_{ts} denote the trajectory success event. An action a_i

¹https://huggingface.co/datasets/xlangai/ubuntu_osworld_verified_trajs

Task Category	Success Traj.	Failed Traj.	Good Actions	Bad Actions
Multi-apps	17	19	23	22
LibreOffice Calc	17	17	20	17
VS Code	14	16	23	19
Chrome	16	14	24	24
LibreOffice Impress	14	14	20	16
GIMP	15	11	20	16
LibreOffice Writer	12	14	15	14
OS	14	12	13	15
VLC	12	8	16	10
Thunderbird	8	8	8	11
Total	139	133	182	164

Table 2. Annotation distribution of trajectories and actions across task categories in CUARewardBench.

is considered correct if $p(o_{ts}|o_{i+1}, a_i) > p(o_{ts}|o_i)$. Conversely, for incorrect steps, $p(o_{ts}|o_{i+1}, a_i) < p(o_{ts}|o_i)$, indicating that additional actions are required to mitigate the negative effects of a_i . For redundant actions, $p(o_{ts}|o_{i+1}, a_i) = p(o_{ts}|o_i)$. However, during our annotation process, we observed that redundant actions cause significantly less harm than incorrect actions, while being considerably more difficult to identify reliably. To enhance annotation objectivity, we focus primarily on distinguishing between correct and incorrect actions, largely excluding redundant actions from our evaluation. Furthermore, we do not annotate every action in the trajectories selected from Section 2.2. Instead, we focus on steps that are critical to trajectory success. Formally, we define two types of key actions:

- *Key Good Actions*: Actions where $p(o_{ts}|o_{i+1}, a_i) - p(o_{ts}|o_i)$ is as large as possible and $p(a_i|o_i)$ is as small as possible. Intuitively, these represent actions that significantly advance task completion while being non-obvious choices.
- *Key Bad Actions*: Actions where $|p(o_{ts}|o_{i+1}, a_i) - p(o_{ts}|o_i)|$ is as large as possible and $p(a_i|o_i)$ is as large as possible. These represent actions that substantially hinder task success while appearing deceptively reasonable.

Annotation Statistics. As shown in Table 2, our final dataset comprises 139 successful and 133 failed trajectories for trajectory-level evaluation, and 182 good and 164 bad actions for action-level assessment across all task categories. For trajectory-level annotations, although OSWorld [3] provides script-based trajectory success evaluation, we employ human annotation to ensure annotation reliability and maintain high-quality standards. For action-level annotations, we selectively annotate key actions following the criteria outlined in the previous section, focusing on steps that are most critical for trajectory success evaluation. Notably, we further annotate bad actions within successful trajectories and good actions within failed trajectories, recognizing that trajectory success and step correctness are orthogonal. This enables robust evaluation of reward models across varying trajectory contexts.

3 Reward Performance and Analysis

3.1 Implementations

Reward model implementation involves two key dimensions: VLM and prompt. Our CUARewardBench systematically evaluates both to provide comprehensive insights into CUA RM.

VLM Selection . Considering the practical application scenarios of CUARewardBench—large-scale data

construction and online reinforcement learning training—we primarily evaluate open-source models. This choice not only reduces the implementation difficulty for reproducing our research but also considers the feasibility of large-scale deployment in real-world applications. We evaluate four categories of models (7 models in total):

- *General VLMs*: We assess the Qwen2.5VL series [15], which represents the leading open-source vision-language models. We evaluate three variants within this series: 7B, 32B, and 72B parameters.
- *Visual Reasoning Models*: We include GLM-4.5V-106B [16], a mixture-of-experts model with 12B activated parameters. This model not only possesses general visual understanding capabilities but also demonstrates strong CUA performance (achieving 35.8% on OSWorld).
- *Specialized CUA Models*: CUA models are endowed with extensive CUA-related knowledge, intuitively suggesting they should possess CUA trajectory evaluation capabilities. However, most CUA models fail to follow instructions for trajectory evaluation, which we attribute to catastrophic forgetting caused by extensive CUA data during post-training. GUI-OWL [4] series represents an exception, built upon Qwen2.5VL with post-training data mixing CUA training and general reasoning data. This approach enables strong CUA capabilities (GUI-OWL-7B achieves 29.4% on OSWorld) while maintaining robust reasoning abilities. We evaluate both GUI-OWL-7B and 32B as reward models.
- *Specialized CUA Reward Models*: World State Model of SE-Agent [6] (SE-WSM) is the only existing open-source CUA-specialized reward model, based on Qwen2.5VL-7B with dedicated CUA reward training. Its training data comprises 860 trajectories from 43 feasible Chrome tasks in OSWorld, executed by UI-TARS and Gemini-2.5-Pro, and automatic annotated by GPT-4o.

Prompt Template. Among existing works, we identify three that have open-sourced their prompt templates for CUA reward modeling:

- *ORM prompt of ZeroGUI* [8]: ZeroGUI designs a frame-by-frame captioning followed by holistic analysis prompt template, requiring Qwen2.5VL-32B to evaluate whether trajectories accomplish their tasks. We adopt ZeroGUI’s prompt template as CUARewardBench’s ORM prompt template.
- *Step reflector prompt of OpenCUA* [7]: OpenCUA employs Claude as a reflector in their chain-of-thought data annotation pipeline, generating reflections for current steps based on previous step reasoning and current screenshots. Considering the coupling complexity between the reflector and previous step reasoning, and to ensure fair comparative experiments, we simplify the reflector prompt as CUARewardBench’s PRM prompt template. The detailed comparison before and after simplification is provided in Section 7.2.
- *Prompt of SE-WSM* [6]: SE-WSM conducts step-by-step analysis of input trajectories, providing multi-dimensional evaluations including trajectory correctness, redundant steps, first error step, and correct action suggestions. This comprehensive evaluation covering both coarse and fine-grained assessments enables it to function as both ORM and PRM. We adopt SE-WSM’s prompt template for both ORM and PRM evaluation in CUARewardBench.

Detailed prompt templates and model output parsing methods are provided in Section 7.2 .

Evaluation Metrics. Existing evaluation frameworks have adopted different metric combinations for assessing reward models. AgentRewardBench [17] primarily focuses on precision, while SE-WSM [6] employs precision and NPV (Negative Predictive Value). To comprehensively evaluate reward model performance, we consider two primary use cases: offline trajectory filtering and online reward provision in reinforcement learning. In the first scenario, precision reflects the proportion of trajectories correctly identified as successful by the reward model, indicating reward reliability. Recall measures the coverage of

Metric	Formula	Interpretation	Assessment Aspect
Precision	$TP / (TP + FP)$	proportion of predicted positive cases that are actually positive	reward reliability
NPV	$TN / (TN + FN)$	proportion of predicted negative cases that are actually negative	reward reliability
Recall	$TP / (TP + FN)$	proportion of actual positive cases that are correctly predicted	sample efficiency
Specificity	$TN / (TN + FP)$	proportion of actual negative cases that are correctly predicted	sample efficiency

Table 3. Evaluation metrics for CUA reward models. TP = True Positive (correctly predicted positive cases), FP = False Positive (incorrectly predicted positive cases), TN = True Negative (correctly predicted negative cases), FN = False Negative (incorrectly predicted negative cases).

actual positive trajectories, representing sample efficiency. For the second scenario, since negative samples with low rewards also contribute to model updates in RL, we introduce NPV and Specificity metrics. These metrics serve as counterparts to precision and recall, reflecting the reliability of negative reward signals and sample efficiency for negative cases, respectively.

As summarized in Table 3, we employ four complementary metrics to comprehensively assess reward model performance. Since reward reliability is more critical than sample efficiency in both offline trajectory filtering and online RL scenarios, we prioritize precision and NPV as primary evaluation metrics, with recall and specificity serving as secondary indicators in our subsequent benchmarking analysis.

3.2 Effect of VLM Selection

Model size and training quality comprehensively impact reward model performance. 1) Across all evaluated models—including general VLMs, specialized CUA models VLMs, and specialized CUA reward models—7B variants consistently underperform their 32B+ counterparts across different metrics. While CUA-specific training enhances the reward prediction capabilities of 7B models (e.g., GUI-OWL-7B vs. Qwen2.5VL-7B in Table 4 and Table 5), they still lag behind larger models. 2) Surprisingly, Qwen2.5VL-72B underperforms compared to the 32B variant, with particularly notable differences in action-level evaluation. A possible explanation is that Qwen2.5VL-32B received additional RL training compared to the 72B model², which improved its reasoning capabilities and consequently led to stronger generalization for CUA reward prediction.

Visual reasoning capability is the core element of CUA reward models. GUI-OWL-32B, despite being post-trained from Qwen2.5VL-32B specifically for CUA tasks, consistently underperforms its base model across all prompt configurations. Through detailed response analysis, we observe that GUI-OWL-32B produces significantly shorter reasoning processes compared to Qwen2.5VL-32B, indicating that despite incorporating general reasoning data during post-training, the model still experiences some degradation in reasoning capabilities. The superior performance of GLM-4.5V-106B over all other models further corroborates this finding, as it maintains the strongest visual reasoning abilities among the evaluated models.

CUA policy training benefits reward evaluation capabilities, but only when reasoning abilities are preserved. GUI-OWL exhibits a performance paradox: GUI-OWL-7B significantly outperforms Qwen2.5VL-7B, while GUI-OWL-32B shows notable degradation compared to Qwen2.5VL-32B. This counterintuitive pattern stems from the differential impact of CUA specialization on models with varying baseline reasoning capabilities. For Qwen2.5VL-7B, which possesses inherently weak reasoning abilities, the benefits gained

²<https://huggingface.co/Qwen/Qwen2.5-VL-32B-Instruct>

Reward Model	Overall					vscode		gimp		writer		chrome		multi_apps	
	P	NPV	R	S	OA	P	NPV	P	NPV	P	NPV	P	NPV	P	NPV
<i>zerogui</i>															
Qwen2.5VL-7B	60.8	65.0	74.8	49.2	62.1	47.8	57.1	57.1	40.0	46.7	54.5	72.2	72.7	93.3	85.7
Qwen2.5VL-32B	70.9	76.1	80.6	65.2	72.8	75.0	85.7	68.8	60.0	53.3	63.6	70.0	80.0	85.0	100.0
Qwen2.5VL-72B	70.0	72.1	75.5	66.2	71.0	65.0	90.0	70.6	66.7	60.0	62.5	66.7	77.8	88.9	94.4
GLM-4.5V-106B	76.8	90.4	92.8	70.7	82.0	73.7	100.0	75.0	100.0	66.7	81.8	72.7	100.0	89.5	100.0
GUI-OWL-7B	69.0	68.8	71.9	65.6	68.4	70.6	83.3	61.9	60.0	64.3	75.0	66.7	77.8	88.2	88.9
GUI-OWL-32B	69.0	73.7	78.4	63.2	71.0	64.3	68.8	65.0	66.7	61.5	69.2	73.7	81.8	100.0	100.0
<i>sewsm</i>															
Qwen2.5VL-7B	63.1	57.1	50.4	69.2	59.6	50.0	54.5	66.7	47.1	46.7	54.5	70.6	69.2	84.6	73.9
Qwen2.5VL-32B	80.0	71.7	69.1	82.0	75.4	84.6	82.4	75.0	57.1	63.6	66.7	75.0	71.4	87.5	85.0
Qwen2.5VL-72B	78.6	74.5	74.1	78.9	76.5	85.7	87.5	78.6	66.7	54.5	60.0	78.9	90.9	100.0	86.4
GLM-4.5V-106B	82.9	77.6	77.0	83.5	80.1	78.6	81.2	75.0	70.0	69.2	76.9	84.2	100.0	92.9	81.8
GUI-OWL-7B	68.4	72.4	76.8	63.2	69.9	66.7	66.7	64.7	55.6	52.6	71.4	76.2	100.0	84.2	94.1
GUI-OWL-32B	75.0	71.4	71.2	75.2	73.2	70.0	65.0	68.8	60.0	90.0	81.2	77.8	83.3	85.0	100.0
SE-WSM-7B	70.0	52.2	20.1	91.0	54.8	100.0	57.1	62.5	44.4	66.7	56.5	88.9	61.9	100.0	55.9
<i>voting-majority</i>															
G106-s 2runs	84.3	70.7	65.5	87.2	76.1	76.9	76.5	71.4	58.3	70.0	68.8	88.2	92.3	100.0	76.0
Q32-s + G106-s	90.1	68.5	59.0	93.2	75.7	90.9	78.9	87.5	55.6	62.5	61.1	92.3	76.5	92.3	78.3
Q32-s + G106-s + G106-z	81.6	84.8	86.3	79.7	83.1	80.0	86.7	73.7	85.7	68.8	90.0	72.7	100.0	93.8	90.0
<i>voting-strict_unanimous</i>															
G106-s 2runs	84.3	82.3	65.5	76.7	71.0	76.9	86.7	71.4	75.0	70.0	76.9	88.2	100.0	100.0	90.0
Q32-s + G106-s	90.1	84.2	59.0	72.2	65.4	90.9	85.7	87.5	83.3	62.5	90.0	92.3	100.0	92.3	89.5
Q32-s + G106-s + G106-z (UPE)	89.8	93.3	56.8	63.2	59.9	90.9	100.0	87.5	100.0	57.1	90.0	92.3	100.0	92.3	100.0

Table 4. Performance comparison of outcome reward models (ORM) across different vision-language models, prompt configurations, and task categories. Results show precision (P), negative predictive value (NPV), recall (R), and specificity (S) for trajectory success evaluation under two prompt configurations (*zerogui* and *sewsm*) and two voting strategies (*voting-majority* and *voting-strict_unanimous*). In model names, “-z” denotes *zerogui* prompt and “-s” denotes *sewsm* prompt; “Q32” denotes Qwen2.5VL-32B and “G106” denotes GLM-4.5V-106B. Due to space constraints, complete results across all task categories are provided in Table 8.

from CUA training outweigh the negative effects of reasoning capability degradation. Conversely, for Qwen2.5VL-32B with strong baseline reasoning capabilities, the negative impact of reasoning degradation overshadows the gains from CUA training. This finding suggests that CUA policy training can enhance reward evaluation performance, but only when the specialization process preserves the model’s fundamental reasoning abilities. These implications inform both CUA policy training and reward model development, suggesting that incorporating sufficient high-quality general reasoning data during CUA training is essential to maintain the model’s reasoning capabilities and thereby ensure effective reward evaluation performance.

Specialized CUA reward models require diverse training data to achieve effective generalization. SE-WSM [6], a specialized CUA reward model fine-tuned from Qwen2.5VL-7B, shows overall performance on CUARewardBench that is comparable to, but slightly worse than, its Qwen2.5VL-7B base model. This underperformance likely stems from its narrowly scoped training data coverage, which comprises only 860 trajectories from 43 Chrome tasks. While this narrow scope may suffice for web-only benchmarks like AgentRewardBench [17], it proves inadequate for generalizing to the comprehensive task categories covered in our CUARewardBench. The comprehensive task-category coverage and policy model diversity in CUARewardBench successfully expose limitations that remain hidden in more limited evaluation settings, demonstrating its effectiveness as a rigorous testbed for CUA RM capabilities.

3.3 Impact of Prompt Templates

Prompt templates primarily influence P-NPV trade-offs rather than overall performance improvements. As shown in Tables 4 and 5, different prompt templates create distinct evaluation standards that affect the

Reward Model	Overall					vscode		gimp		writer		chrome		multi_apps	
	P	NPV	R	S	OA	P	NPV	P	NPV	P	NPV	P	NPV	P	NPV
<i>opencua_reflector</i>															
Qwen2.5VL-7B	54.4	49.4	53.8	50.0	52.0	53.6	42.9	59.1	50.0	54.5	50.0	44.0	43.5	63.2	57.7
Qwen2.5VL-32B	60.3	64.8	79.8	41.5	61.7	58.3	66.7	76.2	73.3	60.0	66.7	57.1	69.2	62.5	76.9
Qwen2.5VL-72B	58.5	64.8	83.0	34.8	60.1	64.5	72.7	73.1	90.0	54.2	60.0	52.4	66.7	56.2	61.5
GLM-4.5V-106B	64.0	78.5	89.0	44.5	67.9	66.7	88.9	74.1	100.0	57.9	60.0	57.1	69.2	71.0	92.9
GUI-OWL-7B	64.6	61.8	67.0	59.1	63.3	63.6	55.0	66.7	60.0	62.5	61.5	55.2	57.9	66.7	62.5
GUI-OWL-32B	61.6	61.5	71.4	50.6	61.6	62.5	70.0	66.7	66.7	56.2	53.8	59.4	68.8	70.0	64.0
<i>sewsm</i>															
Qwen2.5VL-7B	56.7	54.2	67.0	43.3	55.8	62.5	55.6	50.0	40.9	56.2	53.8	57.1	69.2	55.6	55.6
Qwen2.5VL-32B	65.3	62.4	67.8	59.8	64.0	74.1	80.0	76.5	63.2	69.2	62.5	71.4	66.7	66.7	66.7
Qwen2.5VL-72B	58.7	67.1	85.2	33.5	60.7	60.0	71.4	72.7	71.4	58.3	80.0	56.4	77.8	56.2	61.5
GLM-4.5V-106B	69.5	64.2	66.1	67.7	66.9	68.8	90.0	81.2	65.0	72.7	61.1	80.0	71.4	63.6	60.9
GUI-OWL-7B	56.6	64.2	86.8	26.2	58.1	59.4	60.0	59.3	55.6	54.2	60.0	53.5	80.0	52.6	57.1
GUI-OWL-32B	57.4	68.8	89.0	26.8	59.5	57.9	75.0	64.3	75.0	70.0	88.9	53.8	66.7	55.0	80.0
SE-WSM-7B	58.7	52.0	48.4	62.2	54.9	76.2	66.7	58.3	45.8	70.0	57.9	60.0	57.1	57.9	53.8
<i>voting-majority</i>															
G106-s 2runs	73.6	62.8	59.6	76.2	67.4	72.4	84.6	81.2	65.0	72.7	61.1	85.7	64.7	68.8	58.6
Q32-s + G106-s	75.6	60.5	52.5	81.1	66.0	79.2	77.8	100.0	64.0	85.7	59.1	83.3	61.1	76.5	64.3
Q32-s + G106-s + G106-o	68.4	71.5	78.6	59.8	69.7	71.9	100.0	83.3	72.2	68.8	69.2	80.0	82.6	70.8	71.4
<i>voting-strict_unanimous</i>															
G106-s 2runs	73.6	64.2	59.6	57.9	58.8	72.4	88.9	81.2	68.4	72.7	56.2	85.7	75.0	68.8	59.1
Q32-s + G106-s	75.6	69.1	52.5	46.3	49.6	79.2	100.0	100.0	64.3	85.7	66.7	83.3	84.2	76.5	62.5
Q32-s + G106-s + G106-o (UPE)	81.7	85.1	48.9	24.4	37.3	81.8	100.0	100.0	100.0	83.3	62.5	87.5	100.0	86.7	85.7

Table 5. Evaluation results of process reward models (PRM) for step-level correctness assessment across various vision-language models and prompt configurations. The table presents precision (P), negative predictive value (NPV), recall (R), and specificity (S) metrics under two prompt configurations (*opencua_reflector* and *sewsm*) and two voting strategies (*voting-majority* and *voting-strict_unanimous*). In model names, “Q32” denotes Qwen2.5VL-32B and “G106” denotes GLM-4.5V-106B. Due to space constraints, complete results across all task categories are provided in Table 9.

precision-recall balance. Taking Qwen2.5VL-32B as an example, in ORM settings, the *sewsm* prompt achieves 9.1 percentage points higher precision than *zerogui*, but suffers an 4.4 percentage point drop in NPV. This trade-off pattern is consistently observed in PRM settings, where *sewsm* outperforms *opencua_reflector* by 5.0 percentage points in precision while losing 2.4 percentage points in NPV.

SE-WSM prompt enforces stricter trajectory success criteria compared to ZeroGUI. Through comparative analysis of prompts and model responses, we find that *sewsm* employs stricter success standards than *zerogui*. The *sewsm* template requires VLMs to verify trajectory reasonableness across multiple dimensions, including trajectory correctness, redundant steps, first error identification, and correct action suggestions. These additional evaluation dimensions naturally increase the likelihood that successful trajectories may be incorrectly rejected due to minor imperfections. Conversely, *zerogui* adopts relaxed criteria, requiring only binary trajectory success determination, which allows some failed trajectories to deceive VLMs through superficial reasonableness.

OpenCUA reflector adopts more relaxed action evaluation criteria compared to SE-WSM. The key distinction between *opencua_reflector* and *sewsm* prompts lies in their temporal scope: *opencua_reflector* receives only truncated trajectories up to the current step, limiting its perspective to immediate action effects on current states without global visibility into subsequent steps or overall task impact. This constraint makes the former susceptible to deceptive bad actions that appear reasonable in isolation but prove detrimental to task completion. In contrast, *sewsm* processes complete trajectories, naturally providing stricter constraints for action correctness evaluation through comprehensive temporal context.

3.4 Verification Difficulty in CUA

Reward model remains unreliable for both trajectory- and step-level CUA assessments. Comparing CUA success rates in Table 1 with ORM overall accuracy in Table 4, we observe that while trajectory-level verification asymmetry [18] remains evident, even the best-performing ORM achieves only 82.9% precision and 80.1% overall accuracy, indicating substantial room for improvement. Similarly, Table 5 shows that step-level verification also presents considerable challenges, with reward models demonstrating limited effectiveness in providing reliable step-by-step guidance. These findings reveal that both trajectory-level ORMs and step-level PRMs fall short of ideal performance standards, collectively limiting their capacity to provide reliable supervision signals for CUA training.

3.5 Ensemble Methods

Building upon the insights from previous analyses, we propose **Unanimous Prompt Ensemble (UPE)**, a novel ensemble approach that significantly enhances reward model reliability for CUA tasks. UPE integrates two complementary strategies: (1) a strict unanimous voting mechanism that prioritizes prediction reliability over sample efficiency, and (2) strategic prompt-template configurations that leverage the complementary P-NPV trade-offs identified in Section 3.3. Together, these components enable substantial improvements in both precision and negative predictive value, which are critical metrics for ensuring reliable reward signals in reinforcement learning applications.

Strict Unanimous Voting. While ZeroGUI [8] employs majority voting, our experiments reveal a critical limitation: it improves precision but substantially reduces NPV (e.g., Q32-s + G106-s vs. G106-s in Tables 4 and 5). In CUA training, reward reliability is more critical than sample efficiency. Reduced sample efficiency can be compensated by increased sampling, but unreliable rewards directly compromise RL training quality. Therefore, we introduce **strict unanimous voting**. Extending traditional unanimous voting [19], our strategy requires consensus on both positive and negative predictions: a sample is classified only when all ensemble members unanimously agree; otherwise, it is abstained. Table 6 illustrates the distinction with concrete voting scenarios, comparing how strict unanimous voting and majority voting produce different decisions under identical ensemble configurations. As shown in Table 4 and 5, this approach substantially improves both precision and NPV for ORM and PRM. While recall and specificity decrease, they remain acceptable—a favorable trade-off when reliability outweighs coverage.

Voting Scenario	Majority Voting	Strict Unanimous
2 Pos., 0 Neg.	Positive ✓	Positive ✓
1 Pos., 1 Neg.	Negative ×	No Prediction △
0 Pos., 2 Neg.	Negative ×	Negative ×

Table 6. Comparison between majority voting and strict unanimous voting strategies. ✓ indicates positive prediction, × indicates negative prediction, and △ indicates no prediction when consensus cannot be reached.

Prompt-Template Ensemble. As revealed in Section 3.3, different prompt templates exhibit distinct P-NPV trade-off characteristics. We exploit this complementarity by strategically combining models configured with diverse prompt templates within our voting ensemble. As shown in Table 4, Q32-s + G106-s + G106-z outperforms Q32-s + G106-s: while precision decreases slightly by 0.3 percentage points, NPV increases by 9.1 percentage points. This demonstrates that for ORM, this heterogeneous prompt configuration yields further NPV improvements beyond those achieved by strict unanimous voting strategy alone. For PRM, the benefits are even more pronounced (Q32-s + G106-s + G106-o vs. Q32-s + G106-s in Table 5), with substantial simultaneous gains in both precision and NPV. This synergy between strict unanimous voting and prompt

diversity establishes UPE as an effective method for enhancing reward model reliability in CUA evaluation.

4 Error Analysis

This section provides a comprehensive microscopic analysis of error patterns, examining specific failure modes, and the fundamental limitations that constrain current reward model effectiveness. We analyze 53 failure cases from GLM-4.5V-106B, the best-performing model in ORM evaluation, to identify systematic error patterns. As shown in Table 7, we categorize errors by frequency: reasoning errors (35.8%), visual understanding errors (30.2%), action understanding errors (17.0%), knowledge deficiency (15.1%), and inherent RM limitations (1.9%). We examine each category in detail below.

Error Category	Count	Percentage (%)
Reasoning Error	19	35.8
Visual Understanding Error	16	30.2
Action Understanding Error	9	17.0
Knowledge Deficiency	8	15.1
Inherent RM Limitation	1	1.9
Total	53	100

Table 7. Distribution of error modes of GLM-4.5V-106B as ORM using *sewsim* prompt.

Visual Understanding Errors (30.2%). Reward models frequently misinterpret visual information in screenshots, leading to incorrect assessments of computer states. For instance, when an agent executes the task "adding strike-through sign on the line," it successfully selects and applies strike-through formatting but misses the final few characters. The reward model fails to detect this incomplete execution and incorrectly judges the trajectory as successful.

Action Understanding Errors (17.0%). Under the SE-WSM prompt configuration, reward models infer agent actions from consecutive screenshots to evaluate trajectory success. However, models often derive incorrect actions from adjacent frames. For example, when an agent clicks an "OK" button in a dialog box, the reward model mistakenly believes the agent failed to complete the confirmation operation, leading to an incorrect failure assessment. A straightforward solution involves incorporating coordinate markers in screenshots, as implemented in the OpenCUA reflector approach, which significantly reduces such errors.

Knowledge Deficiency (15.1%). Just as agents frequently fail due to insufficient software operation knowledge, reward models often lack domain-specific knowledge necessary to establish correct task success criteria. For instance, when an agent's task is to "enlarge the text on my screen," the agent incorrectly magnifies the entire screen rather than adjusting text font size. The reward model, unaware that Ubuntu system settings provide distinct options for these operations, incorrectly judges the trajectory as successful.

Reasoning Errors (35.8%). Even when reward models correctly understand visual elements and agent actions while possessing relevant knowledge, they frequently commit logical errors during information synthesis. For example, when an agent successfully completes the task "set the decimal separator as a comma (,)," the reward model initially acknowledges the correct configuration but subsequently engages in convoluted reasoning that leads to overturning its original correct conclusion.

Inherent RM Limitations (1.9%). A small but significant category of errors reveals fundamental limitations of VLM-based reward models: screenshots provide only partial observations of computer states. For instance, when an agent successfully completes the task "use GIMP to compress the image to under 600KB," the screenshot lacks visual feedback about the compressed file size, leaving the reward model without evidence

to verify task completion. This limitation suggests that reward models and script-based verifiers could serve as complementary approaches for more robust reward estimation.

5 Limitations and Future Directions

While CUARewardBench provides a rigorous benchmark for CUA reward model evaluation, our work has several important limitations that warrant discussion:

Limited Practical Validation of UPE Although we propose the UPE method and demonstrate its effectiveness in improving reward reliability (precision and NPV), we have not validated it in actual reinforcement learning training loops. This leaves several critical questions unanswered: (1) Could the trade-off between sample efficiency and reward reliability observed in our benchmark be maintained in the rollouts of actual RL training? (2) Could the samples filtered by UPE exhibit systematic biases, potentially discarding high-value training examples? (3) How does UPE perform across different training stages and policy distributions? These questions require extensive RL training experiments to address.

Benchmark Scale and Scenario Coverage While CUARewardBench establishes rigorous annotation standards, two key limitations constrain its scope: (1) *Limited scale*: With 272 trajectory annotations and 346 step-level annotations, the current benchmark may not fully capture long-tail failure modes or diverse agent strategies. (2) *Task distribution gap*: All tasks are sampled from OSWorld [3], which focuses primarily on limited application scenarios. This creates a gap with real-world computer use, where more diverse and complex workflows are prevalent.

6 Conclusions

This paper presents a systematic investigation into computer-using agent reward models through benchmark construction, empirical analysis, and method development. We introduce CUARewardBench, the first comprehensive benchmark for evaluating reward models on computer-using agents, comprising 272 trajectory annotations and 346 step-level annotations across 10 software categories. Through systematic evaluation of 7 vision-language models with 3 prompt templates, we reveal critical insights into current CUA RM capabilities and limitations. Our key findings include that: (1) model size and training quality comprehensively impact reward model performance; (2) visual reasoning capability is the core element of CUA reward models, with general VLMs outperforming specialized CUA models; (3) prompt templates primarily influence precision-recall trade-offs rather than overall performance improvements; and (4) both trajectory-level and step-level verification face significant challenges, with action-level evaluation proving more difficult than trajectory-level assessment. Error analysis reveals that reasoning errors (35.8%) and visual understanding errors (30.2%) constitute the primary failure modes. Building upon these insights, we propose Unanimous Prompt Ensemble (UPE), a novel ensemble method that significantly enhances reward model reliability through strict unanimous voting and strategic prompt-template configurations. UPE achieves 89.8% precision and 93.3% NPV for ORM, and 81.7% precision and 85.1% NPV for PRM, substantially outperforming single VLMs and traditional ensemble approaches.

Our work establishes both a rigorous evaluation framework and an immediately deployable solution for the community. CUARewardBench provides a standardized testbed for advancing computer-using agent evaluation, while UPE offers a practical method for enhancing reward model reliability in CUA training pipelines. Together, these contributions lay the foundation for developing more reliable reward models to support large-scale CUA training and deployment.

Contributions

Authors Haojia Lin^{1*} Xiaoyu Tan^{1*} Yulei Qin^{1*} Zihan Xu¹ Yuchen Shi¹ Zongyi Li¹ Gang Li¹
Shaofei Cai^{1,2} Siqi Cai¹ Chaoyou Fu³ Ke Li¹ Xing Sun¹

Affiliations ¹Tencent Youtu Lab ²Peking University ³Nanjing University

***Equal Contributions** Haojia Lin Xiaoyu Tan Yulei Qin

Acknowledgments We greatly thank the OSWorld [3, 14] community for open-sourcing the CUA tasks and diverse CUA trajectories.

References

- [1] OpenAI. Introducing operator, January 2025. URL <https://openai.com/index/introducing-operator>.
- [2] Haoming Wang, Haoyang Zou, Huatong Song, Jiazhan Feng, Junjie Fang, Juntong Lu, Longxiang Liu, Qinyu Luo, Shihao Liang, Shijue Huang, et al. Ui-tars-2 technical report: Advancing gui agent with multi-turn reinforcement learning. *arXiv preprint arXiv:2509.02544*, 2025.
- [3] Tianbao Xie, Danyang Zhang, Jixuan Chen, Xiaochuan Li, Siheng Zhao, Ruisheng Cao, Toh J Hua, Zhoujun Cheng, Dongchan Shin, Fangyu Lei, et al. Osworld: Benchmarking multimodal agents for open-ended tasks in real computer environments. *Advances in Neural Information Processing Systems*, 37: 52040–52094, 2024.
- [4] Jiabo Ye, Xi Zhang, Haiyang Xu, Haowei Liu, Junyang Wang, Zhaoqing Zhu, Ziwei Zheng, Feiyu Gao, Junjie Cao, Zhengxi Lu, et al. Mobile-agent-v3: Fundamental agents for gui automation. *arXiv preprint arXiv:2508.15144*, 2025.
- [5] Liang Tang, Shuxian Li, Yuhao Cheng, Yukang Huo, Zhepeng Wang, Yiqiang Yan, Kaer Huang, Yanzhe Jing, and Tiaonan Duan. Sea: Self-evolution agent with step-wise reward for computer use. *arXiv preprint arXiv:2508.04037*, 2025.
- [6] Zeyi Sun, Ziyu Liu, Yuhang Zang, Yuhang Cao, Xiaoyi Dong, Tong Wu, Dahua Lin, and Jiaqi Wang. Seagent: Self-evolving computer use agent with autonomous learning from experience. *arXiv preprint arXiv:2508.04700*, 2025.
- [7] Xinyuan Wang, Bowen Wang, Dunjie Lu, Junlin Yang, Tianbao Xie, Junli Wang, Jiaqi Deng, Xiaole Guo, Yiheng Xu, Chen Henry Wu, et al. Opencua: Open foundations for computer-use agents. *arXiv preprint arXiv:2508.09123*, 2025.
- [8] Chenyu Yang, Shiqian Su, Shi Liu, Xuan Dong, Yue Yu, Weijie Su, Xuehui Wang, Zhaoyang Liu, Jinguo Zhu, Hao Li, et al. Zerogui: Automating online gui learning at zero human cost. *arXiv preprint arXiv:2505.23762*, 2025.
- [9] Tianbao Xie, Jiaqi Deng, Xiaochuan Li, Junlin Yang, Haoyuan Wu, Jixuan Chen, Wenjing Hu, Xinyuan Wang, Yuhui Xu, Zekun Wang, et al. Scaling computer-use grounding via user interface decomposition and synthesis. *arXiv preprint arXiv:2505.13227*, 2025.
- [10] Yan Yang, Dongxu Li, Yutong Dai, Yuhao Yang, Ziyang Luo, Zirui Zhao, Zhiyuan Hu, Junzhe Huang, Amrita Saha, Zeyuan Chen, et al. Gta1: Gui test-time scaling agent. *arXiv preprint arXiv:2507.05791*, 2025.
- [11] Anthropic. Computer use tool, 2025. URL <https://docs.claude.com/en/docs/agents-and-tools/tool-use/computer-use-tool>.
- [12] Yujia Qin, Yining Ye, Junjie Fang, Haoming Wang, Shihao Liang, Shizuo Tian, Junda Zhang, Jiahao Li, Yunxin Li, Shijue Huang, et al. Ui-tars: Pioneering automated gui interaction with native agents. *arXiv preprint arXiv:2501.12326*, 2025.
- [13] Dong Guo, Faming Wu, Feida Zhu, Fuxing Leng, Guang Shi, Haobin Chen, Haoqi Fan, Jian Wang, Jianyu Jiang, Jiawei Wang, et al. Seed1. 5-v1 technical report. *arXiv preprint arXiv:2505.07062*, 2025.
- [14] Tianbao Xie, Mengqi Yuan, Danyang Zhang, Xinzhuang Xiong, Zhennan Shen, Zilong Zhou, Xinyuan Wang, Yanxu Chen, Jiaqi Deng, Junda Chen, Bowen Wang, Haoyuan Wu, Jixuan Chen, Junli Wang, Dunjie Lu, Hao Hu, and Tao Yu. Introducing osworld-verified. *xlang.ai*, July 2025. URL <https://xlang.ai/blog/osworld-verified>.
- [15] Shuai Bai, Keqin Chen, Xuejing Liu, Jialin Wang, Wenbin Ge, Sibao Song, Kai Dang, Peng Wang, Shijie Wang, Jun Tang, et al. Qwen2. 5-v1 technical report. *arXiv preprint arXiv:2502.13923*, 2025.

- [16] Wenyi Hong, Wenmeng Yu, Xiaotao Gu, Guo Wang, Guobing Gan, Haomiao Tang, Jiale Cheng, Ji Qi, Junhui Ji, Lihang Pan, et al. Glm-4.1 v-thinking: Towards versatile multimodal reasoning with scalable reinforcement learning. *arXiv e-prints*, pages arXiv-2507, 2025.
- [17] Xing Han Lù, Amirhossein Kazemnejad, Nicholas Meade, Arkil Patel, Dongchan Shin, Alejandra Zambrano, Karolina Stańczak, Peter Shaw, Christopher J Pal, and Siva Reddy. Agentrewardbench: Evaluating automatic evaluations of web agent trajectories. *arXiv preprint arXiv:2504.08942*, 2025.
- [18] Jason Wei. Asymmetry of verification and verifier’s law. <https://www.jasonwei.net/blog/asymmetry-of-verification-and-verifiers-law>, 2024. Blog post.
- [19] Ludmila I Kuncheva. *Combining pattern classifiers: methods and algorithms*. John Wiley & Sons, 2014.
- [20] Reiichiro Nakano, Jacob Hilton, Suchir Balaji, Jeff Wu, Long Ouyang, Christina Kim, Christopher Hesse, Shantanu Jain, Vineet Kosaraju, William Saunders, et al. Webgpt: Browser-assisted question-answering with human feedback. *arXiv preprint arXiv:2112.09332*, 2021.
- [21] Yiheng Xu, Hongjin Su, Chen Xing, Boyu Mi, Qian Liu, Weijia Shi, Binyuan Hui, Fan Zhou, Yitao Liu, Tianbao Xie, et al. Lemur: Harmonizing natural language and code for language agents. *arXiv preprint arXiv:2310.06830*, 2023.
- [22] Boyu Gou, Ruohan Wang, Boyuan Zheng, Yanan Xie, Cheng Chang, Yiheng Shu, Huan Sun, and Yu Su. Navigating the digital world as humans do: Universal visual grounding for gui agents. *arXiv preprint arXiv:2410.05243*, 2024.
- [23] Zhiyong Wu, Zhenyu Wu, Fangzhi Xu, Yian Wang, Qiushi Sun, Chengyou Jia, Kanzhi Cheng, Zichen Ding, Liheng Chen, Paul Pu Liang, et al. Os-atlas: A foundation action model for generalist gui agents. *arXiv preprint arXiv:2410.23218*, 2024.
- [24] Tianbao Xie, Jiaqi Deng, Xiaochuan Li, Junlin Yang, Haoyuan Wu, Jixuan Chen, Wenjing Hu, Xinyuan Wang, Yuhui Xu, Zekun Wang, et al. Scaling computer-use grounding via user interface decomposition and synthesis. *arXiv preprint arXiv:2505.13227*, 2025.
- [25] Yiheng Xu, Zekun Wang, Junli Wang, Dunjie Lu, Tianbao Xie, Amrita Saha, Doyen Sahoo, Tao Yu, and Caiming Xiong. Aguis: Unified pure vision agents for autonomous gui interaction. *arXiv preprint arXiv:2412.04454*, 2024.
- [26] Yujia Qin, Yining Ye, Junjie Fang, Haoming Wang, Shihao Liang, Shizuo Tian, Junda Zhang, Jiahao Li, Yunxin Li, Shijue Huang, et al. Ui-tars: Pioneering automated gui interaction with native agents. *arXiv preprint arXiv:2501.12326*, 2025.
- [27] Dong Guo, Faming Wu, Feida Zhu, Fuxing Leng, Guang Shi, Haobin Chen, Haoqi Fan, Jian Wang, Jianyu Jiang, Jiawei Wang, et al. Seed1. 5-vl technical report. *arXiv preprint arXiv:2505.07062*, 2025.
- [28] Saaket Agashe, Jiuzhou Han, Shuyu Gan, Jiachen Yang, Ang Li, and Xin Eric Wang. Agent s: An open agentic framework that uses computers like a human. *arXiv preprint arXiv:2410.08164*, 2024.
- [29] Saaket Agashe, Kyle Wong, Vincent Tu, Jiachen Yang, Ang Li, and Xin Eric Wang. Agent s2: A compositional generalist-specialist framework for computer use agents. *arXiv preprint arXiv:2504.00906*, 2025.
- [30] Nathan Lambert, Valentina Pyatkin, Jacob Morrison, LJ Miranda, Bill Yuchen Lin, Khyathi Chandu, Nouha Dziri, Sachin Kumar, Tom Zick, Yejin Choi, et al. Rewardbench: Evaluating reward models for language modeling. *arXiv preprint arXiv:2403.13787*, 2024.
- [31] Yantao Liu, Zijun Yao, Rui Min, Yixin Cao, Lei Hou, and Juanzi Li. Rm-bench: Benchmarking reward models of language models with subtlety and style. *arXiv preprint arXiv:2410.16184*, 2024. doi: 10.48550/arXiv.2410.16184. URL <https://arxiv.org/abs/2410.16184>.

- [32] Michihiro Yasunaga, Luke Zettlemoyer, and Marjan Ghazvininejad. Multimodal rewardbench: Holistic evaluation of reward models for vision language models. *arXiv preprint arXiv:2502.14191*, 2025.
- [33] Tianyi Men, Zhuoran Jin, Pengfei Cao, Yubo Chen, Kang Liu, and Jun Zhao. Agent-rewardbench: Towards a unified benchmark for reward modeling across perception, planning, and safety in real-world multimodal agents. *arXiv preprint arXiv:2506.21252*, 2025.

7 Appendix

7.1 Related Work

Computer-Use Agents. Computer-use agent approaches can be broadly categorized into three methodological paradigms. Text-based language models leverage structured GUI metadata such as DOM trees and accessibility labels to generate symbolic commands, ranging from early page-centric agents [20] to recent language-only planners that avoid raw pixel processing [21]. Vision-centric agents incorporate screen imagery through two main strategies: grounding-focused methods that learn to associate natural-language references with bounding boxes or coordinate clicks [22, 23, 24], and end-to-end policies that directly translate screenshots into action sequences [25, 26, 27]. Agent frameworks represent a third paradigm that enhances large language models with specialized components including vision encoders, hierarchical or search-based planners, episodic memory, and tool APIs to tackle long-horizon tasks requiring integrated perception, reasoning, and control [28, 29].

Reward Models for CUA. OSWorld benchmark [3] initially employed manually predefined scripts to verify agent trajectory success. However, writing custom verification scripts for each task incurs prohibitively high costs, making this approach inadequate for large-scale training datasets or online reinforcement learning systems. Consequently, recent approaches leverage Vision-Language Models (VLMs) as reward models for trajectory verification. These reward model applications can be categorized into two primary paradigms. The first paradigm focuses on *trajectory filtering*, where reward models identify successful trajectories. SEAgent [6] trains a world state model to determine trajectory success and identify the first error step. OpenCUA [7] employs Claude-3.7 for step-by-step reflection, ultimately judging whether trajectories accomplish their assigned tasks. GUI-OWL [4] utilizes both LLMs and VLMs to generate two-channel step-level critics, aggregating these assessments to determine trajectory success. SEA [5] develops a step filtering model to remove erroneous and redundant trajectories from training data. The second paradigm employs reward models to *provide reward signals for reinforcement learning*. UITARS-2 [2] uses the UITARS-2 model itself as an outcome reward model (ORM) for general web task verification in RL settings. SEAgent [6] applies adversarial imitation punishment to first error steps identified by their world state model.

Reward Benchmarks. There is some research evaluating reward models across multiple domains. RewardBench [30] established multi-domain evaluation for LLMs covering chat, reasoning, and safety. RM-Bench [31] introduced Best-of-N evaluation, while Multimodal RewardBench [32] proposed evaluation frameworks for VLMs with expert-annotated triplets. For agents, AgentRewardBench [17] evaluates Web agents but ignores desktop operations, while Agent-RewardBench [33] covers multimodal agents but lacks CUA-specific capabilities like GUI positioning accuracy. In contrast, our CUARewardBench investigates reward model capabilities specifically for computer-using agents, covering desktop software operations and multi-step decision-making that previous benchmarks do not possess.

7.2 Prompts Templates of Reward Models

For ZeroGUI [8] and SE-WSM [6] prompts, we directly adopt the original versions from their open-source implementations, as shown in Figure 3 and Figure 4. For the OpenCUA reflector [7] prompt, we modified the components coupled with step-wise chain-of-thought reasoning to ensure compatibility with our experimental environment. The original and simplified prompts are presented in Figure 5 and Figure 6, respectively.

ORM Prompts of ZeroGUI

You are an expert at analyzing computer usage task completion from screenshots.

You will be given a task instruction and a series of screenshots of the task execution. Please analyze the screenshots and provide a detailed analysis of the task completion by following the steps below:

1. First, analyze and understand the task instruction. Describe what should the screenshots look like if the task is completed successfully.
2. Describe what you observe in each screenshot, analysis what actions were taken and what changes were made to the UI to achieve the task (or mistakes made).
3. When you analyze the screenshots, please pay attention to the very detailed elements and changes in the UI. Every small detail may affect the final result.
4. After all screenshots are analyzed, provide a overall reasoning about how the task was completed or failed at **the final state**. Make sure you have considered all demands of the task instruction.
5. Determine if the task was completed at **the final state** (the last screenshot) successfully (score 1 for success, 0 for failure). If the task is completed during the process but not at the final state, it should be considered as failure (0 score). Provide your response strictly in the following format:

TASK REQUIREMENT:

[Your understanding of the task instruction]

SCREENSHOT ANALYSIS:

Screenshot 1:

[Analysis of first screenshot]

Screenshot 2:

[Analysis of second screenshot]

...

REASONING:

[Your reasoning]

FINAL ANSWER:

[Your final answer]

SCORE: [0/1]

Now, please **strictly follow the format** and analyze the following screenshots (The last line should only be

SCORE: [0/1], no other text):

Task Instruction: {instruction}

Screenshots (by order):

Figure 3. ORM prompt of ZeroGUI [8]. The prompt instructs the vision-language model to analyze computer usage task completion through detailed screenshot examination and structured response formatting.

ORM and PRM Prompts of SE-WSM

You are an expert at analyzing computer usage task completion from screenshots. I am evaluating the performance of a UI agent. The images provided are **sequential keyframes** that represent the full execution trajectory of the agent when attempting to follow a command. These keyframes correspond to the instruction: '{instruction}'. Please thoroughly analyze the sequence to assess the following aspects:

1. **Correctness** — Did the agent successfully complete the task as instructed?
2. **Redundant Steps** — Identify any unnecessary or repeated actions that do not contribute to the goal.
3. **Optimization** — Did the agent follow an efficient plan with a minimal number of steps?
4. **First Error Step** — If the execution is incorrect or sub-optimal, determine the index of the **first keyframe where a mistake occurred**.
5. **Error Analysis** — Provide a brief explanation of the mistake at that step.
6. **Correct Action Suggestion** — Explain what the agent **should have done instead** at the point of error.

Important Instructions:

- The agent may have made progress toward the goal, but unless the task is **fully and correctly completed**, you must set 'Correctness' to **False**.
- Be cautious in determining success. Missing confirmation screens, skipped inputs, or wrong UI elements clicked all count as errors.
- Carefully examine all UI changes, button interactions, text entries, and any visual feedback in the screenshots.
- Clearly indicate **which exact steps are redundant** (starting from 1).

Once you finish the analysis, return your evaluation in the following dictionary format (include your step-by-step reasoning **above** the result):

```
<analysis process>
your step-by-step reasoning
</analysis process>
<res_dict>
{
  "Correctness": True/False,
  "Redundant": [step_num, ...],
  "Optimized": True/False,
  "First_Error_Step": step_num or None,
  "Error_Type": "brief description of the mistake",
  "Correct_Action": "what should have been done instead"
}
</res_dict>
```

Figure 4. SE-WSM [6] prompt template both for ORM and PRM evaluation. The prompt instructs the vision-language model to conduct multi-dimensional assessment including trajectory correctness, redundant steps identification, first error step detection, and correct action suggestions for both ORM and PRM evaluation.

PRM Prompts of OpenCUA Reflector

You are a judge of a computer-use agent. You will be given a task, the agent's history actions, agent last action and thought process with 2 screenshots.

- Thought is the reasoning for the history steps and prediction for the next step. - Action is the summary of the code - Code is the code that will be executed. - The first screenshot is the observation of the last action and the second image is the computer state after executing the last action (code).

Task: {goal}

History steps: {history_steps}

Last step:

Thought: {thought}

Action: {action}

Code: {code}

Your response should include 3 parts:

1. Is the last step redundant: - If the last step is doing unnecessary action or action that is not related to the task, for example, clicking irrelevant places, open irrelevant applications, or unnecessary scrolls, you should mark it as redundant.

2. Is the last step incorrect: - If the action is related to the task but executing the code did not produce the expected change, you should mark it as incorrect. - If the action and the code do not align, you should mark it as incorrect. For example the action tries to click an element but failed according to the screenshot. - The last screenshot shows the application or window is not fully loaded, but the code is executed. - If there is any mistake in the thought action.

3. Reflection: - You should first provide a natural summary of the visual changes between the last screenshot and the current screenshot. If there is no change, please mention it. - If the last step is correct and not redundant, you should then say the step is necessary and how it is effective. - If the last step is incorrect, you should then provide a clear explanation of the error. - If the last step is redundant, you should then provide a clear explanation.

YOUR RESPONSE MUST BE EXACTLY ONE VALID JSON OBJECT. NO MARKDOWN, NO EXTRA TEXT.

Here is the exact JSON structure you must follow:

```
<res_dict>
{
  "last_step_correct": bool,
  "last_step_redundant": bool,
  "reflection": str
}
</res_dict>
```

Figure 5. original PRM Prompts of OpenCUA reflector [7]. The prompt provides comprehensive step-level assessment including thought process analysis, action-code alignment verification, and structured JSON output format for systematic evaluation of agent decision-making processes.

Simplified PRM Prompts of OpenCUA Reflector

You are a judge of a computer-use agent. Your role is to evaluate whether the agent's last action was redundant, incorrect, or appropriate for completing the given task. You will analyze screenshots showing the agent's history, the state before the last action, and the state after the last action, along with the raw code that was executed. You will be given a task, the agent's history screenshots, agent's last action code, and 2 screenshots showing before and after the last action.

- The history screenshots show what happened before the last step, helping you understand the agent's previous progress and context. - The last action is represented by the raw code that was executed. - The before and after screenshots show the state immediately before and after executing the last action code. - Note: If there is mouse related code that needs coordinates, the center of the red circle in the before screenshot shows the position. But do not mention the red circle or red dot in any part of your response. - You will be provided with: history screenshots (showing previous steps), one screenshot before executing the last action, and one screenshot after executing the last action. - You should focus on the differences between the before and after screenshots to understand what the last action accomplished, while using history screenshots to understand the context and detect redundancy.

Task: {instruction}

History screenshots: <image>

Screenshots before and after the last action: <image>

Last action code: Step {step_index}: {action_code}

Your response should include 3 parts:

1. Is the last step redundant: - If the last step is doing unnecessary action or action that is not related to the task, for example, clicking irrelevant places, open irrelevant applications, or unnecessary scrolls, you should mark it as redundant. - If the last step is a repeat of a former step based on the history screenshots, you should mark it as redundant. - Too many scrolls or drags of the scroll bar, or too many clicks of the same button, or too many clicks of the same element, you should mark it as redundant.

2. Is the last step incorrect: - If the action is related to the task but executing the code did not produce the expected change, you should mark it as incorrect. - If the code execution failed or did not work as intended based on the before/after screenshots, you should mark it as incorrect. - The after screenshot shows the application or window is not fully loaded, but the code was executed. - If there is any clear mistake in the action based on what the code was trying to accomplish. - You should carefully examine the click/drag related actions. In many cases, the code wants to click a target, but it doesn't match the element at the center of the red circle in the before screenshot.

3. Reflection: - You should first provide a natural summary of the visual changes between the before and after screenshots. If there is no change, please mention it. - If the last step is correct and not redundant, you should then say the step is necessary and how it is effective toward completing the task. - If the last step is incorrect, you should then provide a clear explanation of the error. - If the last step is redundant, you should then provide a clear explanation of why it's unnecessary given the history.

Once you finish the analysis, return your evaluation in the following dictionary format (include your step-by-step Reflection **above** the result):

<analysis process>

[your step-by-step reflection]

</analysis process>

<res_dict>

{

"last_step_correct": bool,

"last_step_redundant": bool,

"reflection": str

}

</res_dict>

Figure 6. Simplified PRM Prompts of OpenCUA reflector [7]. The prompt instructs the vision-language model to assess individual agent actions by analyzing visual changes between consecutive screenshots and determining whether the latest action is correct, redundant, or necessary for task completion.

Reward Model	Overall					vlc		os		thunderbird		impress		calc	
	P	NPV	R	S	OA	P	NPV	P	NPV	P	NPV	P	NPV	P	NPV
<i>zerogui</i>															
Qwen2.5VL-7B	60.8	65.0	74.8	49.2	62.1	71.4	66.7	61.1	62.5	50.0	50.0	47.6	42.9	65.0	71.4
Qwen2.5VL-32B	70.9	76.1	80.6	65.2	72.8	72.7	55.6	64.3	58.3	100.0	80.0	66.7	77.8	68.2	83.3
Qwen2.5VL-72B	70.0	72.1	75.5	66.2	71.0	83.3	50.0	66.7	63.6	100.0	72.7	63.2	77.8	63.2	66.7
GLM-4.5V-106B	76.8	90.4	92.8	70.7	82.0	91.7	87.5	68.4	85.7	100.0	80.0	70.6	81.8	78.9	86.7
GUI-OWL-7B	69.0	68.8	71.9	65.6	68.4	75.0	50.0	71.4	66.7	80.0	63.6	58.3	56.2	62.5	61.1
GUI-OWL-32B	69.0	73.7	78.4	63.2	71.0	100.0	61.5	68.8	70.0	75.0	75.0	50.0	50.0	59.1	66.7
<i>sewsm</i>															
Qwen2.5VL-7B	63.1	57.1	50.4	69.2	59.6	50.0	35.7	75.0	55.6	60.0	54.5	66.7	62.5	55.6	56.2
Qwen2.5VL-32B	80.0	71.7	69.1	82.0	75.4	75.0	50.0	81.8	66.7	100.0	72.7	85.7	85.7	78.6	70.0
Qwen2.5VL-72B	78.6	74.5	74.1	78.9	76.5	77.8	54.5	73.3	72.7	66.7	60.0	75.0	68.8	82.4	82.4
GLM-4.5V-106B	82.9	77.6	77.0	83.5	80.1	100.0	53.3	86.7	90.9	100.0	72.7	75.0	83.3	91.7	72.7
GUI-OWL-7B	68.4	72.4	76.8	63.2	69.9	87.5	58.3	64.7	75.0	100.0	80.0	50.0	50.0	63.6	75.0
GUI-OWL-32B	75.0	71.4	71.2	75.2	73.2	85.7	53.8	73.3	72.7	66.7	71.4	62.5	66.7	72.7	60.9
SE-WSM-7B	70.0	52.2	20.1	91.0	54.8	100.0	57.1	33.3	40.0	0.0	50.0	0.0	48.1	33.3	48.4
<i>voting-majority</i>															
G106-s 2runs	84.3	70.7	65.5	87.2	76.1	100.0	53.3	83.3	71.4	100.0	66.7	83.3	75.0	90.0	66.7
Q32-s + G106-s	90.1	68.5	59.0	93.2	75.7	100.0	50.0	90.0	68.8	100.0	66.7	100.0	87.5	87.5	61.5
Q32-s + G106-s + G106-z	81.6	84.8	86.3	79.7	83.1	100.0	61.5	85.7	83.3	100.0	80.0	75.0	83.3	93.8	88.9
<i>voting-strict_unanimous</i>															
G106-s 2runs	84.3	82.3	65.5	76.7	71.0	100.0	53.8	90.0	90.0	100.0	80.0	83.3	85.7	90.0	82.4
Q32-s + G106-s	90.1	84.2	59.0	72.2	65.4	100.0	54.5	90.0	90.0	100.0	80.0	100.0	80.0	87.5	87.5
Q32-s + G106-s + G106-z	89.8	93.3	56.8	63.2	59.9	100.0	83.3	90.0	100.0	100.0	80.0	100.0	87.5	85.7	91.7

Table 8. Supplementary results for Table 4, showing performance of outcome reward models (ORM) on the remaining task categories (vlc, os, thunderbird, impress, calc). Results show precision (P) and negative predictive value (NPV) for trajectory success evaluation under multiple prompt configurations: *zerogui*, *sewsm*, *voting-majority*, and *voting-strict_unanimous*. The Overall metrics remain the same as in Table 4.

7.3 Supplementary Results for Additional Task Categories

This section presents the experimental results for the remaining 5 task categories that were not included in the main paper due to space constraints. These results complement the overall performance and 5 selected categories (VS Code, GIMP, LibreOffice Writer, Chrome, and Multi-apps) shown in Tables 4 and 5, providing complete coverage of all 10 software categories in CUARewardBench.

The supplementary categories include LibreOffice Calc, LibreOffice Impress, VLC, Thunderbird, and OS operations. These results maintain consistency with the patterns observed in the main text, further validating our key findings.

7.4 Use of Large Language Models

In accordance with ICLR 2026 policy, we disclose that Large Language Models (LLMs) were used in the preparation of this paper. Specifically, LLMs were employed to polish the writing, including improving clarity, grammar, and overall presentation of the content. The LLMs were used solely as writing assistance tools and did not contribute to the conceptual or technical aspects of the research.

Reward Model	Overall					vlc		os		thunderbird		impress		calc	
	P	NPV	R	S	OA	P	NPV	P	NPV	P	NPV	P	NPV	P	NPV
<i>opencua_reflector</i>															
Qwen2.5VL-7B	54.4	49.4	53.8	50.0	52.0	62.5	40.0	47.1	54.5	30.0	44.4	71.4	54.5	55.6	47.4
Qwen2.5VL-32B	60.3	64.8	79.8	41.5	61.7	68.4	57.1	55.0	66.7	42.9	60.0	71.4	66.7	50.0	38.5
Qwen2.5VL-72B	58.5	64.8	83.0	34.8	60.1	75.0	83.3	45.5	50.0	41.7	57.1	60.0	50.0	58.8	62.5
GLM-4.5V-106B	64.0	78.5	89.0	44.5	67.9	72.7	100.0	47.8	60.0	50.0	80.0	72.2	61.1	64.5	100.0
GUI-OWL-7B	64.6	61.8	67.0	59.1	63.3	76.5	66.7	55.6	70.0	71.4	75.0	76.5	63.2	61.9	56.2
GUI-OWL-32B	61.6	61.5	71.4	50.6	61.6	70.0	66.7	55.0	75.0	42.9	58.3	61.9	53.3	57.9	50.0
<i>sewsm</i>															
Qwen2.5VL-7B	56.7	54.2	67.0	43.3	55.8	73.7	71.4	42.1	44.4	33.3	42.9	75.0	68.8	51.7	37.5
Qwen2.5VL-32B	65.3	62.4	67.8	59.8	64.0	76.5	66.7	53.3	57.1	55.6	70.0	58.3	50.0	47.8	35.7
Qwen2.5VL-72B	58.7	67.1	85.2	33.5	60.7	72.7	100.0	45.0	50.0	50.0	80.0	60.0	54.5	54.8	50.0
GLM-4.5V-106B	69.5	64.2	66.1	67.7	66.9	76.5	66.7	53.8	56.2	57.1	66.7	61.9	53.3	73.3	59.1
GUI-OWL-7B	56.6	64.2	86.8	26.2	58.1	66.7	60.0	48.0	66.7	70.0	88.9	58.6	57.1	56.7	57.1
GUI-OWL-32B	57.4	68.8	89.0	26.8	59.5	66.7	60.0	50.0	66.7	46.7	75.0	57.6	66.7	53.8	45.5
SE-WSM-7B	58.7	52.0	48.4	62.2	54.9	75.0	60.0	30.8	40.0	33.3	50.0	56.2	45.0	50.0	43.5
<i>voting-majority</i>															
G106-s 2runs	73.6	62.8	59.6	76.2	67.4	86.7	72.7	60.0	57.9	66.7	62.5	61.9	53.3	76.9	58.3
Q32-s + G106-s	75.6	60.5	52.5	81.1	66.0	85.7	66.7	55.6	55.0	57.1	66.7	58.8	47.4	66.7	50.0
Q32-s + G106-s + G106-o	68.4	71.5	78.6	59.8	69.7	77.8	75.0	47.1	54.5	50.0	63.6	62.5	58.3	59.3	60.0
<i>voting-strict_unanimous</i>															
G106-s 2runs	73.6	64.2	59.6	57.9	58.8	86.7	57.1	60.0	50.0	66.7	63.6	61.9	54.5	76.9	64.7
Q32-s + G106-s	75.6	69.1	52.5	46.3	49.6	85.7	66.7	55.6	60.0	57.1	70.0	58.8	62.5	66.7	50.0
Q32-s + G106-s + G106-o	81.7	85.1	48.9	24.4	37.3	92.3	100.0	55.6	100.0	57.1	100.0	80.0	57.1	75.0	100.0

Table 9. Supplementary results for Table 5, showing performance of process reward models (PRM) on the remaining task categories (vlc, os, thunderbird, impress, calc). Results show precision (P) and negative predictive value (NPV) for step-level correctness assessment under multiple prompt configurations: *opencua_reflector*, *sewsm*, *voting-majority*, and *voting-strict_unanimous*. The Overall metrics remain the same as in Table 5.